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Abstract

Computer self-efficacy is known to operate at multiple levels, from application-specific sub-domains like spreadsheets to a judgment of ability for the entire computing domain (general computer self-efficacy-GCSE). Conventional wisdom and many recent studies contend that the level of self-efficacy (specific to general) should match the level of its related constructs to maximize predictive power (Bandura, 1997; Chen, et al., 2001; Pajares, 1996). This thinking claims, for example, that GCSE should be used with a general attitude like computer anxiety (and vice versa). This study examines whether such a limitation is theoretically and empirically sound, given that SE judgments generalize across domains. Results indicate any self-efficacy judgment (specific or general) significantly relates to both general **and** domain-specific constructs. These results suggest that an individual's cognitive processing of ability level is multi-faceted; that is, every SE judgment consists of general and specific components. Evidence further suggests that CSE is simultaneously generalizable and formative in nature.

Keywords
Cognitive psychology, computer self-efficacy, general self-efficacy, specific self-efficacy, computer attitudes, computing competence

INTRODUCTION

The exploration of the relationship between the individual and computers by researchers and practitioners has evolved into a significant stream of knowledge and research concerning the individual and his/her perceptions, beliefs and capabilities concerning technology. The reference discipline for much of this work rests in social and cognitive psychology, where the basic premise is that an individual behaves in a predictable way that is a function of environmental and/or cognitive factors. One influential model was Bandura's (1986) Social Cognitive Theory, which explained human behavior in terms of a continuous reciprocal interaction between cognitive, behavioral, and environmental determinants. This "triadic reciprocality" suggests that behavior is simultaneously a function of, and a determinant of, environmental and cognitive factors (p. 23). Among the most prominent of the cognitive factors is self-efficacy, which is an individual's perception of ability to successfully carry out a task or activity. Self-efficacy is not just an ability perception; it provides a generative mechanism that orchestrates the motivation and effort required to complete the task. It helps determine which activities are attempted, the effort in pursuing that activity, and persistence when encountering obstacles (Bandura, 1986, 1997; Gist and Mitchell, 1992). Self-efficacy also applies to computing behavior. Computer self-efficacy, defined as an individual's judgment of computing capability, is a significant influence in attitudes toward technology (Harrison and Rainer, 1992) and performance (Agarwal, Sambamurthy, and Stair, 2000).

Self-efficacy has been shown to operate at multiple levels; for example, an individual can make judgments of ability for specific applications (such as database or spreadsheet self-efficacy) or a judgment of ability for the entire computing domain,

labeled general computer self-efficacy, or GCSE[1] (Marakas, Yi, and Johnson, 1998). These levels, frequently labeled as specific or general CSE, have been operationalized and used in numerous studies, with varying degrees of success.
Although extant studies confirm a linkage between self-efficacy and various computing behaviors, there is relatively little research which empirically examines the distinctions between general and specific self-efficacy and in particular, their predictive validity. Which level of self-efficacy, for example, should be used in a given study? Research maintains that the level of self-efficacy (specific to general) should match the level of the study outcomes (Ajzen, 1991; Pajares, 1996). Chen, Gully, and Eden (2001) refer to this as "specificity matching" and maintain that matching levels is crucial for predictive power (p. 64).

Although this approach makes intuitive sense, there have been several studies in the IS field where cross-leveling (using different levels for self-efficacy and outcomes) have been significant. For example, GCSE (using the instrument of Compeau and Higgins, 1995a), had a significant relationship with spreadsheet ease of use (Agarwal et al., 2000), affect and anxiety (Compeau, Higgins, and Huff, 1999), and word processing/spreadsheet declarative knowledge (Compeau and Higgins, 1995b).

We contend that the reason for these findings is due to the nature of self-efficacy judgments and the way specific and general judgments interact. The relationship between specific and general self-efficacy has been largely unexplored. Although it is generally accepted that one of the three dimensions of self-efficacy, the generality dimension, is the degree to which SE applies to other domains (Bandura, 1997; Gist and Mitchell, 1992), we believe that the way this operates in individuals is primarily through the relationship between general and specific self-efficacy. But how these influences occur and their impact on the way an individual perceives his ability in any domain has not been empirically examined.

This paper empirically examines the nature of self-efficacy judgments. While antecedent factors which influence the formation of any self-efficacy judgment are well known (e.g., mastery and vicarious experiences, Bandura, 1986), the components of an actual SE judgment require clarification. We propose that AS-CSE judgments (such as spreadsheet SE) consist in part of the individual's perception of ability for the entire computing domain (or GCSE), which is the generality dimension. This occurs through a process we call the "generality effect". We believe this is why some studies have significant cross-leveling results. A clarification of the interaction between self-efficacy judgments is crucial to our understanding of the cognitive processing which occurs in individuals and will further awareness in an area important to organizations.

GCSE AND GENERALITY DIMENSION

GCSE is an individual judgment of ability across all computing domains (Marakas et al., 1998). Compeau and Higgins (1995a) describe it as a perception of ability for different hardware and software configurations. It is not application specific, but rather is an individual's overall ability belief regarding the entire computing domain. Conceptually, it can be considered the sum of all computer sub-domain CSEs (Marakas et al., 1998). This point is worth noting: GCSE is formed from the SE judgments of all constituent domains in computing (e.g., AS-CSEs). This was demonstrated empirically in a study where AS-CSEs were summed into a GCSE which demonstrated significant relationships with outcome variables (Downey, 2006). We call this the "contribution effect".

Self-efficacy has three distinct but related dimensions, including strength, magnitude, and generality (Bandura, 1986; Compeau and Higgins, 1995a). Strength is an assessment of confidence in successfully completing a task. Magnitude (called "level" by Bandura), refers to task difficulty levels. The third dimension, generality, is the degree to which the self-efficacy judgment applies to other tasks in other domains. Eden and Kinnar (1991) consider generality as that which transfers among domains; it is described as a "product of a lifetime of experience ... not amenable to change under short-lived conditions" (p. 772). We contend that what transfers between specific domains is GCSE. As an individual makes specific CSE judgments, those judgments are influenced by their perception of overall computing ability. We call this the generality effect which we define as the process by which general SE of encompassing domains influence SE judgments of related sub-domains. Some depict GCSE as a trait, which suggests it is slow to change and influences multiple activities (Agarwal et al., 2000; Bandura, 1997).

How this process occurs is complex and not the intent of this study. However Bandura (1997) lists five processes through which generality occurs, including the existence of similar sub-skills in domains and developing generic self-judgment skills

[1] In this study, application-specific forms of self-efficacy are labeled AS-CSE while general SE will be labeled GCSE.

that apply to all self-efficacy judgments, like assessing task demands or evaluating possible courses of action to accomplish the task.

We intend to demonstrate the generality effect in this study obliquely by empirically establishing that cross-level relationships are significant. We consider empirically cross-level relationships a worthwhile endeavor in itself, considering the literature which recommends specificity matching. Conceptually we believe GCSE judgments transfer to specific judgments. If cross-level relationships are significant, that is AS-CSEs are significant predictors of general level outcomes, and GCSE significantly predicts domain specific performance, this suggests that there is an interaction between the judgments of self-efficacy. We contend that the reciprocal interaction between GCSE and component domain CSEs undermines the theoretical soundness of specificity matching and suggests a generality effect.

THEORETICAL MODEL AND HYPOTHESES

This study compares the predictive power of general and AS-CSEs by examining the strength of their relationships with common outcomes. To allow a comparison of cross-level relationships, some outcomes are general and some domain-specific. The theoretical model is presented in Figure 1. The model suggests that general level outcomes (attitudes and overall computing competence), and specific-level outcomes (application-specific competence and performance), are a function of *both* GCSE and AS-CSEs.

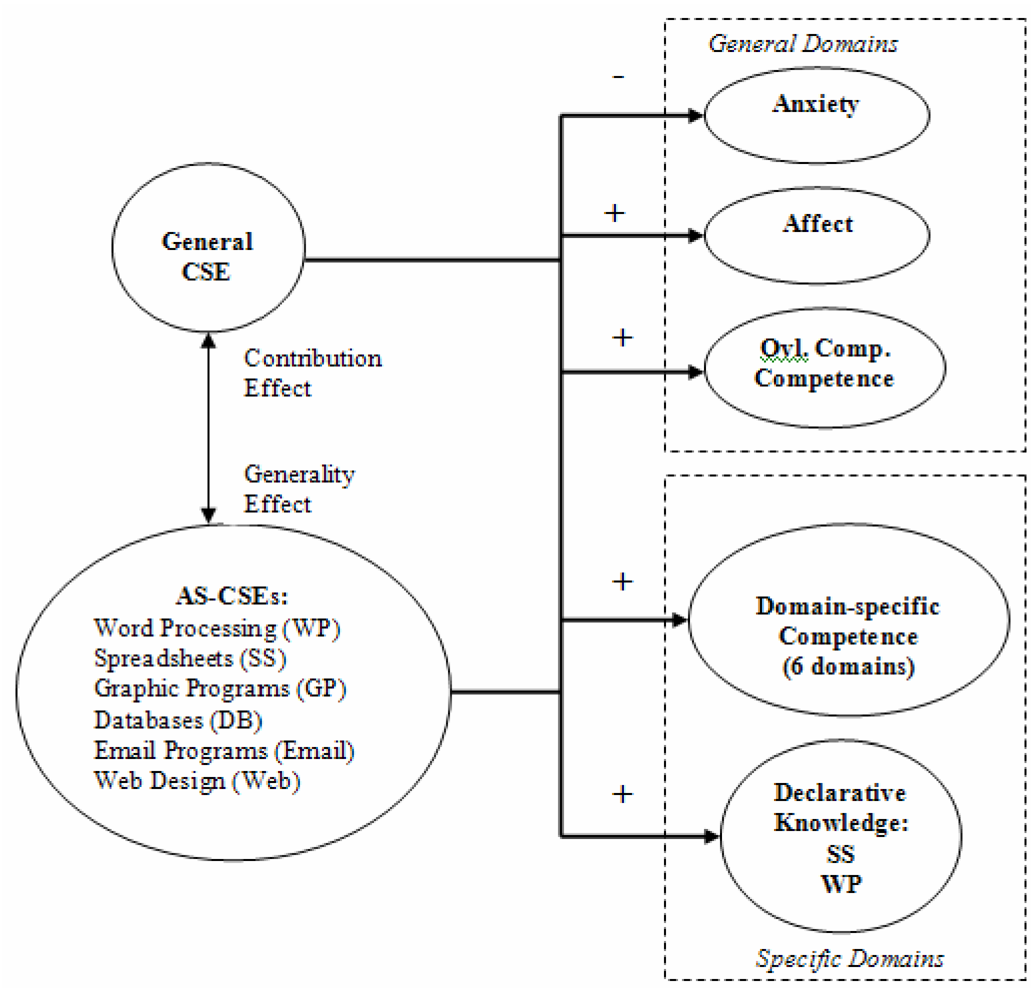

Figure 1. Theoretical Model

According to specificity matching, AS-CSEs should be significant predictors of domain specific competence and GCSE should be a significant predictor of general domain outcomes. The generality effect suggests that an individual's judgment of efficacy for AS-CSEs is in part a function of the individual's GCSE (displayed as the down pointed arrow in the figure).

When an individual judges their ability in a specific domain, part of the cognitive processing that occurs includes their perceived ability in the full domain (Marakas et al., 1998). Given the linkage between GCSE and AS-CSEs, we contend that GCSE should have a significant relationship with domain-specific outcomes, including competencies. Similarly, because AS-CSEs contribute to GCSE, AS-CSEs should have significant relationships with general computer outcomes.

Outcomes of CSE (Attitudes and Competence)

An attitude has been defined as “a learned predisposition to respond in a consistently favorable or unfavorable manner” towards a domain (Fishbein and Ajzen, 1975, p. 6). It is an internal state that influences personal choice (Gagne, 1984). Computer attitudes influence how an individual reacts to the computing environment. Both theory and research suggests that there is a significant relationship between CSE and computer attitudes. How an individual “feels” about a domain, their emotional arousal towards the domain, is influenced by what he thinks his capability is in that domain (Marakas et al., 1998).

Computer Anxiety

Computing anxiety is a fear of computers or of computer use (Loyd and Gressard, 1984). Computer anxiety is influenced by a variety of emotional and environmental factors (Marakas et al., 1998). Self-efficacy influences how individuals interpret their experiences, which influences anxiety and other emotions (Bandura, 1997). Studies show that persons with high CSE have less anxiety, while those with low CSE exhibit higher anxiety (Johnson and Marakas, 2000). This leads to the first hypothesis:

> **Hypothesis 1**: Both GCSE and AS-CSEs will have a negative relationship with computer anxiety, a general level construct.

Computer Affect

Another computing attitude that has received attention is that of affect, or the feeling of like or dislike towards computing. Affect is a different construct than anxiety (Kernan and Howard, 1990). An individual could simultaneously dislike computing and have little anxiety towards it. A person’s attitude towards computing is a critical factor in user acceptance as well as computer usage (Al-Jabri and Al-Khaldi, 1997). Individuals tend to pursue activities they like while avoiding disliked activities. Affect, and in particular positive affect or computer liking, has a significant relationship with CSE (Rainer and Harrison, 1993). Therefore:

> **Hypothesis 2**: Both GCSE and AS-CSEs will have a positive relationship with computer affect (liking), a general level construct.

Computing Competence

The relationship between self-efficacy and performance is one of the strongest in the literature. Individuals with higher self-efficacy tend to perform better at tasks in question and have higher competence (Bandura, 1997; Compeau and Higgins, 1995b; Munro, Huff, Marcolin, and Compeau, 1997). The acquisition of skills or competencies is accomplished through a process which includes gaining declarative knowledge, integrating this knowledge, and putting it to use through procedural knowledge (Kanfer and Ackerman, 1989). Declarative knowledge is understanding “facts and things” (Anderson, 1985, p. 199), or “verbal knowledge” (Kraiger, Ford, and Salas, 1993). Self-efficacy influences each phase of skill acquisition (Marcolin, Compeau, Munro, and Huff, 2000). Competence may be measured at either the general level (full or overall computing domain) or at individual application levels (e.g., spreadsheet competence). Both GCSE and AS-CSEs should significantly influence competence at either level. Therefore:

> **Hypothesis 3**: Both GCSE and AS-CSEs will have a positive relationship with overall computer competence (a general level construct) and application-specific competence and performance (domain-specific constructs).

RESEARCH METHODOLOGY

The population for this study is Midshipmen in the U.S. Navy’s commissioning program. This research was part of an ongoing study to determine the effectiveness of technology training for newly commissioned officers. There are 57 universities that currently have a Naval Reserve Officers Training Corps program as well as the US Naval Academy, with Midshipmen in the process of earning college degrees and receiving commissions in the Navy or Marine Corps. The Naval Academy (because of its size) plus thirteen universities with NROTC programs were chosen at random to participate from across the U.S. Each university was sent 24 surveys, while the Naval Academy received 61. Of the 373 surveys sent, 310 completed responses were received for an overall response rate of 83%. The average age of respondent was 21.1 (sd = 2.91); 267 were male (86%) and 45 were female. On average, responders had 2.4 years of college (sd = .99).

Study Measures

Attitudes

Anxiety and affect were measured using the anxiety and computer liking subscales of the Computer Attitude Scale developed by Loyd and Gressard (1984). This instrument was validated by Al-Jabri and Al-Khaldi (1997). Woodrow (1991) stated that the subscales were reliable enough to be administered separately. Both scales used a seven-point scale, where 1 is "completely disagree" and 7 is "completely agree".

Computing Competence

Computer competence was measured at both an overall level (entire computing domain) as well as six individual application domains, using an instrument adapted by Munro et al. (1997). The application domains included word processing (abbreviated in this paper as WP), spreadsheets (SS), graphics programs (GP), databases (DB), email programs and web page development. The instrument asked respondents the number of domain packages they used, number of courses taken in the domain, and thoroughness of current knowledge of the domain (on a scale of 0 = "No Knowledge", to 7 = "Complete Knowledge"). For overall computing competence, the six application domains were added to the respondent's reported expertise in two other domains, "other" software and hardware (several items each).

Declarative Knowledge

Declarative knowledge was measured for the domains of word processing and spreadsheets using an actual fifteen item multiple choice test. The items were specific to the applications of Microsoft Word and Microsoft Excel. The items on each test were derived from the "intermediate" level of expertise provided from Microsoft (Microsoft Corporation, 2003). Care was taken to eliminate confounding by an application effect, where a respondent could score below their actual knowledge level because they had expertise in a non-Microsoft application. Each respondent indicated the application they knew best and only those who indicated Word and Excel were included. Each survey recipient received only one of the performance tests, randomly divided. The performance test was optional, but 202 respondents completed one of the tests (out of 310, a 65% return). Of these, 97 usable tests on Excel and 105 usable tests on Word were received.

Application CSEs

Application-specific CSE was calculated for each of the six application domains. All of the items in each of the six scales were task-based and started with the same stem, "I believe I have the ability to…", followed by the actual task within the domain. Following the recommendation of Bandura (1986), each AS-CSE included both magnitude ("Yes" or "No") and strength (1-10). Following the recommendation of Lee and Bobko (1994), each application CSE score was derived from averaging the strength of only those tasks that the respondent believed they could accomplish.

The AS-CSE (spreadsheet) instrument was developed by Johnson and Marakas (2000). The other five AS-CSEs were self-developed, but similar in scope and design to the spreadsheet scale. All were pilot tested successfully; reliability and validity are provided in the results section (factor analysis in the appendix).

GCSE

GCSE was measured using the ten item GCSE instrument of Compeau and Higgins (1995a). This instrument uses the "unfamiliar" software stem with an unspecified task. Like each AS-CSE instrument, this scale also included magnitude and strength and the score was derived in the same manner.

ANALYSES OF FINDINGS

Measurement Model

To assess the measurement model, we first examined the reliability and factor structures of each construct, followed by convergent and discriminant validity.

CSE Scales

Each of the six CSE measures was factor analyzed independently. Results indicated that all six AS-CSE constructs were unidimensional and every item in each scale loaded most highly on the applicable latent construct, suggesting convergent validity. Four items were eliminated due to low factor loadings (two from WP-CSE, one each from SS-CSE and GP-CSE). When GCSE was factor analyzed, however, the scale was two-dimensional. To retain a one dimensional construct, two of the ten items were eliminated (items 9 and 10). Reliabilities were high. Table 1 presents construct means, standard deviations, and correlations of all CSE scales.

Construct	Mean	SD	Reliability	Correlations and Average Variance Extracted						
				(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) WP-CSE	9.12	1.42	.95	**.88**						
(2) SS-CSE	7.47	2.60	.97	.45	**.90**					
(3) GP-CSE	7.68	1.87	.95	.63	.55	**.88**				
(4) DB-CSE	3.59	3.23	.99	.12*	.40	.21	**.95**			
(5) Email-CSE	8.86	2.05	.92	.58	.34	.51	.18	**.89**		
(6) Web-CSE	5.30	3.60	.98	.30	.40	.25	.49	.31	**.93**	
(7) GCSE	6.87	1.83	.93	.43	.48	.41	.39	.32	.39	**.85**
Off diagonal elements are correlations. Shaded elements along the diagonal represent the square root of AVE (average variance shared between the construct and their measures). All correlations significant at p < .01 except one indicated by * (significant at p < .05).										

Table 1. Descriptive Data CSE Scales

Next, validity was assessed. All seven SE scales were factor analyzed simultaneously. Each item loaded highest on its own construct, rather than other variables, suggesting construct validity (Netemeyer, Bearden, and Sharma, 2003). Factor loadings are provided in the Appendix. Average variance extracted (AVE) was then computed. AVE should be greater than .50 to justify using a construct and discriminant validity is indicated if its square root is greater than other construct correlations (Fornell and Larcker, 1981). The shaded diagonal elements in Table 1 provide results of this test, indicating satisfactory validity.

Attitude Scales

The two attitude scales were examined in a like manner as the CSE scales. Anxiety (mean = 1.83; sd = 1.0) and liking (mean = 4.73; sd = 1.2) had a correlation of -.58. Reliabilities were .92 and .91 respectfully. Each item loaded on its own factor. An analysis using square root of AVE indicated sufficient discriminant validity .88, greater than correlation of -.58.

Competence and Knowledge Scales

Computer competence was measured for six application domains and for overall computing, plus there were two performance tests in the domains of word processing and spreadsheets. Means, standard deviations, and correlations are provided in Table 2 for the six application domains and overall computing competence.

Construct	Mean	SD	Correlations						
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Email Competence	7.81	2.3	1.0						
(2) WP Competence	7.39	1.9	.64	1.0					
(3) GP Competence	5.49	2.2	.55	.55	1.0				
(4) SS Competence	5.11	2.0	.46	.54	.58	1.0			
(5) Web Competence	2.84	3.3	.40	.40	.35	.38	1.0		
(6) DB Competence	2.06	2.4	.29	.33	.34	.42	.45	1.0	
(7) Ovl Competence	53.9	22.1	.68	.69	.66	.68	.66	.61	1.0
n = 310. All correlations significant at p < .01									

Table 2. Descriptive Data for Competencies

Respondents' competence levels ranged from higher competence (WP and Email) to lower competence (DB and Web). All correlations were significant between domain competencies, suggesting in part the similarities present in these software applications (such as the Windows environment).

Because each respondent received only one of the objective performance tests, and to ensure there was no distribution effect, t-tests were conducted to determine if there were any differences between the group that received (and returned) the WP test, the group returning the SS test, and the group that returned neither. Tests indicated there were no significant differences between the groups in major, age, gender, college class, or university attending. The WP objective test (n = 105; mean = 7.80; sd = 2.5) had a correlation with the WP competence measure of .367 (p < .01). The SS test (n = 97; mean = 9.50; sd = 3.6) had a correlation with the spreadsheet competence measure of .596 (p < .01). The high correlations, particularly in the spreadsheet domain, provide some degree of convergent validity.

Hypotheses Testing

Given a satisfactory measurement model, the hypotheses were then tested. Regression analysis was chosen (instead of SEM) in order to facilitate testing the *differences* in predictive power of various self-efficacy measures on general and specific outcomes using the Cohen and Cohen (1983) multiple regression procedure.

Hypotheses testing were conducted in two steps and presented in Tables 3 (general outcomes) and 4 (specific outcomes). First, simple regressions were run between the indicator (independent or IV) variables and each dependent variable (DV) to ascertain whether each CSE significantly predicted the dependent outcome. This step provides an initial assessment of whether all CSEs (general and specific) significantly predict both general and domain-specific outcomes. The second step consisted of determining whether there was a significant difference in predictive strength between GCSE and AS-CSEs for both general and specific outcomes. If specificity matching is sound, GCSE should be a significantly better predictor of general outcomes and AS-CSEs should be significantly better in predicting specific outcomes. This step was accomplished by running a multiple regression which included both CSEs to determine the strongest predictors and then conducting a formal t-test procedure to test the difference. For the general outcomes, the multiple regressions included as IVs both GCSE and all six AS-CSEs. For the specific outcomes, multiple regressions included GCSE and one AS-CSE (the one that matched the domain; for example, with DB competence as the DV, DB-CSE and GCSE were used as IVs). Only those IVs which significantly predicted the DV are included in the multiple regression columns of Table 3.

	Anxiety					Computer Affect					Overall Competence				
	Simple Regression		Multiple Regression		t-test diff.	Simple Regression		Multiple Regression		t-test diff.	Simple Regression		Multiple Regression		t-test diff.
					GCSE vs. AS-CSE					GCSE vs. CSE					GCSE vs. CSE
GCSE	32	-.484	7	6				1	7		93	44	1	1	
WP-CSE	91	-.440				29	64				75	21			
SS-CSE	49	-.389				75	22	5	6	3.28 p < .01	96	46	3	3	538
GP-CSE	38	-.436	4	6	1.61	13	40				98	48	3	6	1.08
DB-CSE	32	-.189				78	85				11	62	3	4	1.44
Email-CSE	94	-.444	4	0	1.04	62	54				36	73			
Web-CSE	75	-.280				25	57	7	5	4.12 p < .01	05	55	2	5	821

n = 310. All regressions shown significant at p < .01. For multiple regressions, only significant IVs are included.

Table 3. General Outcome Results

Using the multiple regression results, a formal t-test was then conducted which compared the predictive power of significant IVs in accordance with the multiple regression procedure of Cohen and Cohen (1983). The t-test is given by Equation (1):

$$t = \frac{\beta_i - \beta_j}{SE\beta_i - \beta_j} \qquad SE\beta_i - \beta_j = \sqrt{\frac{1 - R^2}{n - k - 1}(r^{ii} + r^{jj} - 2r^{ij})} \qquad (1)$$

where β *are* standardized regression coefficient, R^2 is squared multiple correlation, r is the inverse correlation (from the inverse correlation matrix), k is number of independent variables, and n is number of observations.

For general outcomes, results indicate that all self-efficacies, application-specific and general, had a significant relationship with all general outcomes. This demonstrates that specific measures of CSE also predict general outcomes. This provides support for hypotheses 1-3. In the test to determine whether GCSE or AS-CSEs were stronger predictors, results varied by DV. For two of the three, anxiety and overall competence, there was no significant difference between the predictive strength of GCSE and significant AS-CSEs. This suggests that both forms of CSE have relationships with anxiety and overall competence that are similar in strength. For computer liking, there was a difference. The general instrument was significantly stronger than either of the two significant AS-CSEs (web and spreadsheets).

	Simple Regression				**Multiple Regression**				**t-test difference**
	GCSE		AS-CSE		GCSE		AS-CSE		GCSE vs. AS-CSE
	R^2	β	R^2	β	β	t	β	t	
WP Competence	.177	.424	.225	.477	.267	4.99	.361	6.73	t = 1.03 NS
SS Competence	.174	.420	.454	.675	.123	2.59	.616	12.96	t = 5.70 p < .01
GP Competence	.107	.332	.222	.474	.165	3.03	.406	3.03	t = 2.61 p < .01
DB Competence	.108	.333	.370	.610	.115	2.38	.566	11.65	t = 5.32 p < .01
Email Competence	.130	.365	.143	.382	.269	5.01	.295	5.50	t = .300 NS
Web Competence	.127	.361	.418	.648	.129	2.76	.597	12.77	t = 5.68 p < .01
WP Performance Test	.071	.283	.156	.406	.148	1.49	.327	3.29	t = 1.07 NS
SS Performance Test	.235	.493	.370	.613	.200	2.02	.495	5.00	t = 1.65 NS
n = 310 for all competencies; n = 105 for WP test; n = 97 for SS test.									

Table 4. Specific Outcomes Results

For the domain-specific outcomes (note that in Table 4 the DVs are in rows), both GCSE and the appropriate AS-CSE significantly predicted all DVs. Using the t-tests from the multiple regression results, for half of the DVs GCSE was a significantly stronger predictor and for the other half the AS-CSE was stronger. For both actual performance tests, there was no significant difference in the self-efficacy instrument.

DISCUSSION, LIMITATIONS, AND CONCLUSION

This study was designed to examine self-efficacy judgments and the relationship between them. When an individual makes domain-specific computer self-efficacy judgments, these judgments are made within a cognitive context that takes into account (among other factors) past experiences in the domain, task demands, and their perception of ability for the entire computing domain (GCSE). We posited that the process by which this occurs, which we call the generality effect, implies that one component of a specific CSE judgment is the GCSE element. It was also suggested that the relationship between general and specific CSE is reciprocal, that specific CSEs influence or form GCSE (Downey, 2006; Marakas et al., 1998). To demonstrate this, we hypothesized that GCSE should significantly influence domain-specific performance and AS-CSEs should significantly influence general outcomes. This study also clarifies the concept of specificity matching, at least with respect to the computing domain.

Results of the study confirm these hypotheses. GCSE was a significant predictor of all three general outcomes (anxiety, affect, and overall computer competence) but also of *all* specific domain competencies (and performance tests). Specific CSEs were significant predictors of specific competencies, but also of *all* three general-level outcomes. Because cross-level relationships were significant, and because the strength of the predictive power in some cases was not significantly different, this suggests that there is a reciprocal relationship among specific and general CSE. Therefore, we believe a person's judgments of CSE are multi-faceted: specific-CSEs influence GCSE and GCSE generalizes to specific CSE judgments.

This study extends previous research in two ways. First the notion that self-efficacy measures and outcomes should be the same level (i.e., specificity matching) is called into question. Cross level relationships were always significant and in some cases there was no difference in predictive power between same level and cross level relationships (true for anxiety, overall computing competence, word processing test and competence, email competence, and spreadsheet test). It was not true for affect and four specific competencies.

Secondly, this study clarifies the relationship between specific and general CSE. Previous studies have noted positive correlations between the two, but this study suggests that this relationship is also mediated by an individual's ability level in the domain. The influence of GCSE was similar to that of AS-CSE in the domains of email and word processing, the two domains with the highest ability levels. For the other four domain competencies, specific CSE was significantly stronger. This suggests that as an individual masters a domain (such as WP), the influence of WP-CSE weakens and the influence of GCSE gains strength. For domains not mastered, specific CSE is stronger. Further study on the effect of domain ability in this relationship is warranted.

There are several limitations that should be mentioned. As with any cross-sectional instrument, common method bias and other related limitations arise. Attempts were made to reduce the influence of these biases and limitations, by including multiple items for each measure to increase reliability and validity (Netemeyer et al., 2003). The use of two objective performance tests was another method used to mitigate the extent of common method variance. Generalizability to a general population must be approached with caution. This population is one in a Navy commissioning program and may be different from the American population at large. In particular there was a gender discrepancy in this sample. While gender bias could exist, there was no difference between the two gender populations in this study for any demographic variable (age, class, major, or college), indicating that bias was not present.

Given the design of this study, the proposed interaction between self-efficacy judgments cannot be proved. This limitation is common to most cross-sectional studies where the dependent variable was not directly manipulated. Alternative explanations cannot be ruled out. Although the results suggest this to be the case, further study is paramount to make such a conclusion.

The conventional wisdom of matching specificities (SE and outcomes) in studies is called into question by the results of this study. We believe CSE judgments are multi-faceted, that there is a reciprocal interaction between general and specific SEs which reduces the enhanced predictive power when levels are matched. In some cases, according to this study, this interaction is sufficient to offset completely any advantage gained in predictive power by specificity matching.

We posit these relationships in Figure 2. General CSE transfers to all sub-domain CSEs**.** Although what transfers to each sub-domain CSE may be identical, its influence on how an individual uses it to make sub-domain SE judgments appears to be different (and indicated by a different sized GCSE portion). This study indicated that individual's rely on GCSE more in making SE judgments for domains where they had more ability (such as email and word processing).

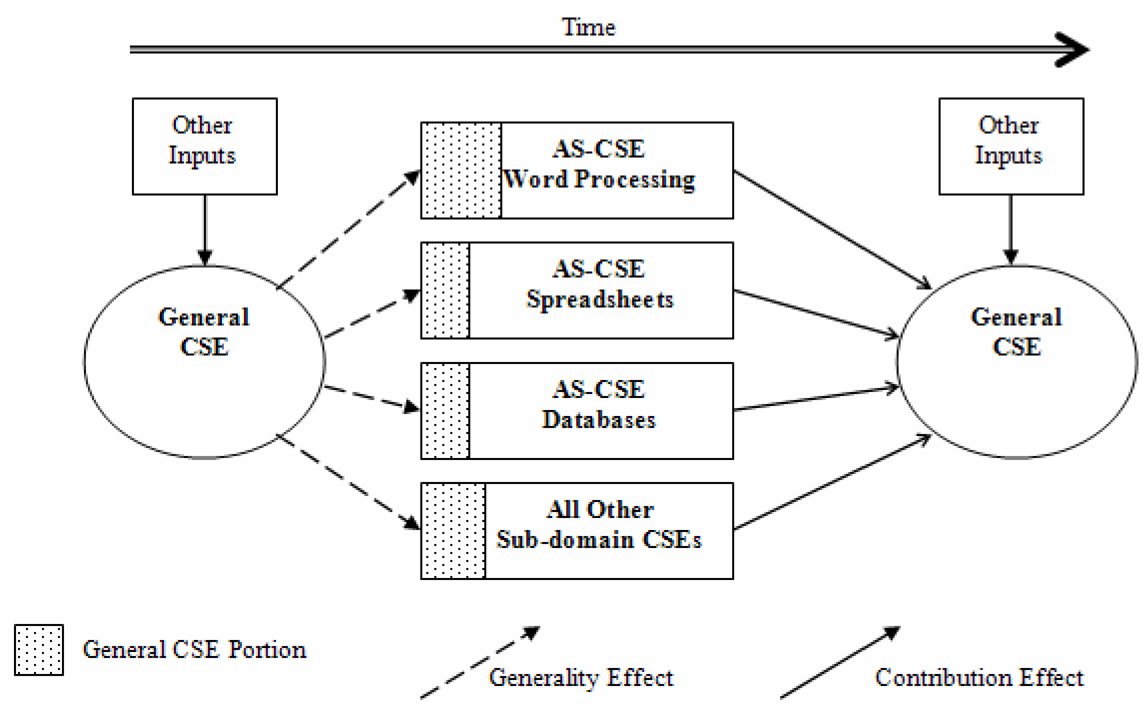

Figure 2. Proposed Relationship among CSEs

Our goal in this study is to further refine the nature of computer self-efficacy and in particular the relationship between its general and specific forms. We believe that understanding the interaction between these levels of efficacy will lead to a greater awareness of the cognitive processes that occur in individuals. This should assist both practitioners and researchers in training environments were SE remains one of the most useful constructs. This study also provides empirical evidence which suggests that single dimension scales (GCSE or application specific) may be used in studies involving any level (general or specific) outcomes.

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APPENDIX

Note: All loadings greater than .30 are displayed							
	1	**2**	**3**	**4**	**5**	**6**	**7**
GCSE1						**.77**	
GCSE2						**.76**	
GCSE3						**.82**	
GCSE4						**.82**	
GCSE5						**.74**	
GCSE6						**.76**	
GCSE7						**.72**	
GCSE8						**.67**	
WP1				**.74**	.32		
WP2				**.77**			.33
WP3				**.77**	.32		.33
WP4				**.71**			
WP5				**.72**			
WP6				**.78**			
WP7				**.72**			
WP8				**.78**			
WP9				**.72**			
SS1			**.74**				
SS2			**.79**				
SS3			**.80**				
SS4			**.84**				
SS5			**.82**				
SS6			**.85**				
SS7			**.84**				
SS8			**.81**				
SS9			**.74**				
GP1				.30	**.81**		
GP2					**.81**		
GP3					**.76**		
GP4				.32	**.81**		
GP5					**.80**		
GP6					**.79**		
GP7					**.68**		
DB1	**.88**						
DB2	**.89**						
DB3	**.91**						
DB4	**.89**						
DB5	**.88**						
DB6	**.87**						
DB7	**.91**						
DB8	**.92**						
DB9	**.91**						
DB10	**.90**						
EM1							**.75**
EM2							**.88**
EM3							**.85**
EM4							**.76**
EM5							**.86**
Web1		**.85**					
Web2		**.85**					
Web3		**.88**					

Web4		**.86**					
Web5		**.89**					
Web6		**.88**					
Web7		**.86**					
Web8		**.85**					

Appendix Table 1. Factor Analyses of all CSE Constructs